Third Generation Teleassistance: Intelligent Monitoring Makes the Difference

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Abstract. Elderly people aim to preserve their independence and autonomy at their own home as long as possible. However, as they get old the risks of disease and injuries increase making critical to assist and provide them the right care whenever needed. Unfortunately, neither relatives, private institutions nor public care services are viable long-term solutions due to the large amount of required time and cost. Thus, smart teleassistance solutions must be investigated. In particular, IoT paradigm helps in designing third generation teleassistance systems by relying on sensors to gather the more data as possible. Moreover, we claim that providing IoT solutions of intelligent monitoring improves the overall efficacy. In this paper, we presents an intelligent monitoring solution, fully integrated in a IoT-based teleassistance system, showing how it helps in giving better support to both end-users and carers. Thanks to intelligent monitoring, carers can instantly access to the relevant information regarding the status of the end-user, also receiving alarms in case of any anomaly or emergency situations have been detected.

1 Introduction

In the last decade, the Internet of Things (IoT) paradigm rapidly grew up gaining ground in the scenario of modern wireless telecommunications [6]. Its basic idea is the pervasive presence of a variety of things or objects (e.g, tags, sensors, actuators, smartphones, everyday objects) that are able to interact with each other and cooperate with their neighbors to reach common goals. IoT solutions have been investigated and proposed in several fields [7], such as automotive [17], logistics [19], agriculture [31], entertainment [18], and independent living [12].

Several research issues are still open: standardization, networking, security, and privacy [27]. We claim that research might also focus on intelligent techniques to improve IoT solutions thus making the difference with respect to classical systems. In other words, artificial intelligence algorithms and methods may be integrated in IoT systems: to allow better coordination and communication among sensors, through adopting multi-agent systems [1]; to adapt the sensor network according to the context, by relying, for instance, on deep learning techniques [16]; as well as to provide recommendations to the final users, by using data fusion and semantic interpretation [4].

Considering the dependency care sector as a case study, in this paper we show how intelligent monitoring techniques, integrated in a IoT-based teleassistance system (namely, eKauri[3]), help in providing better assistance and support to people that need assistance. eKauri is a teleassistance system composed of a set of wireless sensors connected to a gateway (based on Raspberry-pi) that collects and securely redirects them to the cloud. It is worth noting that eKuari is composed by the following kinds of sensors: one presence-illumination-temperature sensors (i.e., TSP01 Z-Wave PIR) for each room, and one presence-door-illumination-temperature sensor (i.e., TSM02 Z-Wave PIR) for each entry door. Intelligent monitoring in eKauri allows to detect the following events: leaving home; going back to home; receiving a visit; remaining alone after a visit; going to the bathroom; going to sleep; and awaking from sleep. In this paper, we focus on the contribution of the intelligent monitoring in eKauri, the interested reader may refer to [23] for a deep description of the system.

The rest of the paper is organized as follows. In Section 2, we briefly recall IoT solutions to teleassistance. Section 3 illustrates how intelligent monitoring improves teleassistance in the eKauri system. In Section 4, the main installations of eKauri are presented together with users' experience. Section 5 ends the paper summarizing the main conclusions.

2 Related Work

Teleassistance remotely, automatically and passively monitors changes in people's condition or lifestyle, with the final goal of managing the risks of independent living [9] [2]. In other words, thanks to teleassistance, end-users are connected with therapists and caregivers as well as relatives and family, allowing people with special needs to be independent.

There are several of efforts to utilize IoT-based systems for monitoring elderly people, most of which target only certain aspects of elderly requirements from a limited viewpoint. Gokalp and Clarke reviewed monitoring activities of daily living of elderly people comparing characteristics, outcomes, and limitations of 25 studies [15]. They found that adopted sensors are mainly environmental, except for accelerometers and some physiological sensors. Ambient sensors could not differentiate the subject from visitors, as opposed to wearable sensors [8] [5]. On the other hand, the latter could only distinguish simple activities, such as walking, running, resting, falling, or inactivity [3]. Moreover, wearable sensors are not suitable for cognitively impaired elderly people due to the fact that they are likely to be forgotten or thrown away [11] [14]. Their main conclusion regarding sensors is that daily living activity monitoring requires use of a combination of ambient sensors, such as motion and door sensors.

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3 Intelligent Monitoring Makes the Difference

Filtering and analyzing data coming from teleassistance systems is becoming more and more relevant. In fact, a lot of data are continuously gathered and sent through the sensors. The role of therapists, caregivers, social workers, as well as relatives (hereinafter, carers) is essential for remotely assisting monitored users. On the one hand, the monitored user (e.g., elderly or disabled people) needs to be kept informed about emergencies as soon as they happen and s/he has to be in contact with therapists and caregivers to change habits and/or to perform some therapy. On the other hand, monitoring systems are very important from the perspective of carers. In fact, those systems allow them to become aware of user context by acquiring heterogeneous data coming from sensors and other sources. Thus, intelligent solutions able to understand all those data and process them to keep carers aware about their assisted persons are needed, providing also users empowerment.

In the following, we show how intelligent monitoring helps in: improving sensors reliability allowing better activity recognition; providing useful information to carers; and inferring quality of life of users.

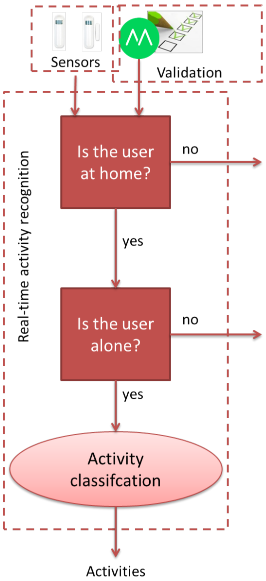

Figure 1. The hierarchical approach to presence detection.

3.1 Improving Sensors Reliability

Performance of IoT systems depends, among other characteristics, on the reliability of the adopted sensors. In the case of teleassistance, binary sensors are quite used in the literature and also in commercial solutions to identify user's activities. Binary sensors do not have the ability to directly identify people and can only present two possible values as outputs ("0" and "1"). Typical examples of binary sensors deployed within smart environments include pressure mats, door sensors, and movement detectors. A number of studies reporting the use of binary and related sensors have been undertaken for the purposes of activity recognition [26]. Nevertheless, sensor data can be considered to be highly dynamic and prone to noise and errors [25]. In the following, we present two solutions that rely on machine learning to improve reliability of sensors in presence detection and sleeping recognition, respectively.

3.1.1 Presence Detection

Detecting user's entering/leaving home can be done by relying on door sensors. Fusing data from door- and motions-sensors could help also in recognizing if the user received visits. Unfortunately, as said, sensors are not 100% reliable: sometimes they loose events or detect them several times. When sensors remain with a low battery charge they get worse. Moreover, also the Raspberry pi may loose some data or the connection with Internet and/or with the sensors. Also the Internet connection may stop working or loose data. Finally, without using a camera or wearable sensors we are not able to directly recognize if the user is alone or if s/he has some visits.

In order to solve this kind of limitations with the final goal of improving the overall performance of our IoT-based system that uses only motion and door sensors, we defined and adopt a two-levels hierarchical classifier (see Figure 1) [24]: the upper level is aimed at recognizing if the user is at home or not, whereas the lower is aimed at recognizing if the user is really alone or if s/he received some visits.

The goal of the classifier at the upper level is to improve performance of the door sensor. In fact, it may happen that the sensor registers a status change (from closed to open) even if the door has not been opened. This implies that the system may register that the user is away and, in the meanwhile, activities are detected at user's home. On the contrary, the system may register that the user is at home and, in the meanwhile, activities are not detected at user's home. To solve, or at least reduce, this problem, we built a supervised classifier able to recognize if the door sensor is working well or erroneous events have been detected. First, we revise the data gathered by the sensor-based system searching for anomalies, i.e.: (1) the user is away and at home some events are detected and (2) the user is at home and no events are detected. Then, we validated those data by relying on Moves, an app installed and running on the user smartphone[4]. In fact, Moves, among other functionality, is able to localize the user. Hence, using Moves as an "oracle" we build a dataset in which each entry is labeled depending on the fact that the door sensor was right (label "1") or wrong (label "0").

The goal of the classifier at the lower level is to identify whether the user is alone or not. The input data of this classifier are those that has been filtered by the upper level, being recognized as positives. To build this classifier, we rely on the novelty detection approach [20] used when data has few positive cases (i.e., anomalies) compared with the negatives (i.e., regular cases); in case of skewed data.

The hierarchical approach was part of the EU project BackHome[5]. To train and test it, we consider a window of 4 months for training and evaluation (training dataset) and a window of 1 month for the test (testing dataset). Experiments have been performed at each level of the hierarchy. First, we performed experiments to identify the best supervised classifier to be used at the upper level of the hierarchy. The best performance has been obtained by relying on the SVM (with $\gamma = 1.0$ and $C = 0.452$). Subsequently, we applied the novelty detection algorithm on the data filtered by the classifier at the upper level, to validate the classifier at the lower one. Finally, we measure the performance of the overall approach. We compared the overall results with those obtained by using the rule-based approach in both levels of the hierarchy. Results are shown in Table 1 and point out

[4] https://www.moves-app.com/
[5] www.backhome-fp7.eu

that the proposed approach outperforms the rule-based one with a significant improvement.

Table 1. Results of the overall hierarchical approach with respect to the rule-based one.

Metric	Rule-based	Hierarchical	Improv.
Accuracy	0.80	0.95	15%
Precision	0.68	0.94	26%
Recall	0.71	0.91	20%
F_1	0.69	0.92	23%

3.1.2 Sleep Recognition

We defined the sleeping activity as the period which begins when the user goes to sleep and ends when the user wakes up in the morning. Sleep recognition is aimed at reporting the following information: (i) the time when the user went to sleep and woke up; hereinafter we will refer to them as *go to sleep time* and *wake up time*, respectively; (ii) the number of sleeping activity hours; and (iii) the number of rest hours, which are sleeping activity hours minus the time that the user spent going to the toilet or performing other activities during the night.

Let us note that the simplest way to recognize sleeping activities is relying on a rule-based approach. In particular, the following rules may be adopted: the user is in the bedroom; the activity is performed at night (e.g., the period between 8 pm to 8 am); the user is inactive; and the inactivity duration is more than half an hour. Unfortunately, when moving to the real-world, some issues arise: user movements in the bed might be wrongly classified as awake; rules assumed all users wake up before 8 A.M., which is a strong assumption; and the approach cannot distinguish if the user is, for instance, in the bedroom watching TV or reading a book, thus classifying all those actions as sleeping.

In order to overcome those limitations, an SVM (Radial Basis Function kernel, with $C = 1.0$, $\gamma = 1.0$) has been adopted to classify the periods between two bedroom motions in two classes, awake and sleep [32]. Let us note that awake corresponds to the period in which the user goes to another room; performs activities in the bedroom; or stays in the bedroom with the light switched on. Otherwise, the activity is sleep.

Experiments, performed from May 2015 to January 2016 in 13 homes in Barcelona, show that the adopted machine learning solution is able to recognize when the user is performing her/his sleeping activity. In particular, the proposed approach reaches an F1 of 96%. Moreover, the adopted classifier is able to easily detect the *go to sleep time*, the *wake up time*, the number of sleeping activity hours and the number of rest hours. Figure 2 shows the comparisons between the ground truth (obtained by questionnaires answered by the users) and the results obtained with the machine learning approach (based on an SVM classifier). The plot has as temporal axis (axis x) and each coordinate in axis y represents nights in the dataset. The figure shows, in red, the sleep activity hours according to the ground truth and, in blue, the sleep activity hours calculated by the system. As both sleep activity hours of the same night are plotted in the same y coordinate, if the ground truth and the results coincide the color turns purple. If the *go to sleep time* and/or *wake up time* do not coincide, there is a text next to the corresponding side with the difference between the time coming from the ground truth and that coming from the results. In the middle of each bar there is the total time which results differ from the baseline.

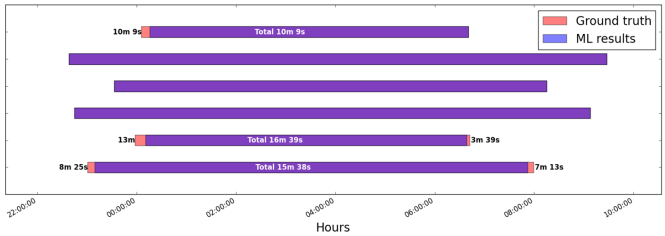

Figure 2. Comparison between the ground truth and the machine-learning (SVM) one.

3.2 Providing Feedback to Carers

The role of carers is essential for remotely assisting people that need assistance. Thus, intelligent monitoring able to understand gathered data and process them to keep carers aware about their assisted persons are needed [13].

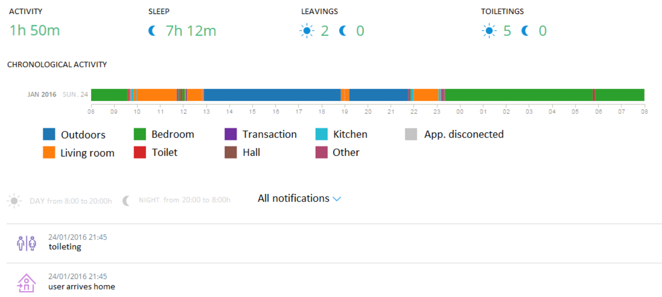

Figure 3. The main information given to carers through the healthcare center.

Thanks to the user-centered approach from the above-mentioned projects, we designed friendly and useful interfaces for accessing and visualizing relevant data and information. In particular, carers identified as the most relevant the following information (see Figure 3, first line on the top): time spent making activities, time spent sleeping, number of times the user leaves the home (during both day and night), and number of times the user goes to toilet (during both day and night). Moreover, they considered relevant to visually show the rooms where the user stayed time after time during a day (see Figure 3, central part) or during a period (e.g., the last month, as shown in Figure 4). They also want to be informed about all the notifications, chronologically ordered (see Figure 3, on the bottom). Finally, they want to access to some statistics to be aware about the evolution of user's habits in order to act accordingly.

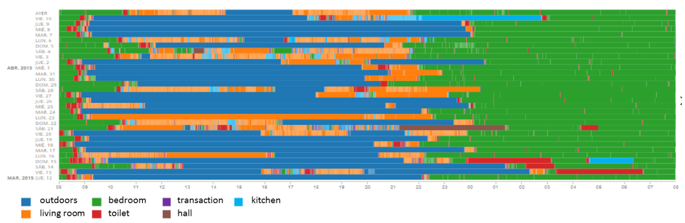

Figure 4. 1 month reporting.

To highlight the relevance of providing suitable information to carers, let us mention here two cases that happened during Barcelona installations in collaboration with Centre de Vida Independent[6]. *Case-1.* A woman with Alzheimer and heart problems needs continuously assistance and, thus, a caregiver visits her daily. One day, eKauri detected that no visits were received, an alarm was generated and the caregiver called. The caregiver confirmed that she did not go to visit the user that day. *Case-2.* During the afternoon, a user is accustomed to go out for a walk. One day, she stayed in the bedroom. eKauri detected the change in her habit and a caregiver called her. Actually, she had a problem with a knee and she could not walk. A physiotherapist was asked to go to visit her.

3.3 Assessing Quality of Life of Users

In the dependency care sector, analyzing data gathered by sensors may help in improving teleassistance systems in becoming aware of user context. In so doing, they would be able to automatically infer user's behavior as well as detect anomalies. In this direction, we studied a solution aimed at automatically assessing quality of life of people [29]. The goal is twofold: to provide support to people in need of assistance and to inform therapists, carers and families about the improvement/worsening of quality of life of monitored people.

First, we defined a Visual Analogic Scale (VAS) QoL questionnaire composed of the following items: *MOOD*, *HEALTH*, *MOBILITY*, *SATISFACTION WITH CARE*, *USUAL ACTIVITIES* (which includes *SLEEPING*), and *PAIN/DISCOMFORT*. Those items have been categorized in two families: monitorable and inferable. Monitorable items can be directly gathered from sensors without relying on direct input from the user. Inferable items can be assessed by analyzing data retrieved by the system when considering activities performed by the user not directly linked with the sensors.

We performed experiments on two monitorable items (i.e., *MOBILITY* and *SLEEPING*) and one inferable (i.e., *MOOD*). In particular, we are able to detect and acknowledge the location of the user over time as well as the covered distance in kilometers and the places where s/he stayed. At the same time, we can detect when the user is sleeping as well as how many times s/he is waking up during the night. Merging and fusing the information related to *MOBILITY* and *SLEEPING*, we may also infer the overall *MOOD*.

The corresponding QoL assessment system is composed of a set of sub-modules, each one devoted to assess a specific QoL item; namely: *MOBILITY*-assessment module; *SLEEPING*-assessment module; and *MOOD*-assessment module. Each sub-module is composed of two parts: Feature Extractor and Classifier. The Feature Extractor receives as input the list of notifications $\{n\}$ and the list of activities $\{a\}$ and extracts the relevant features $\{f\}$ to be given as input to the Classifier. The Classifier, then, uses those features to identify the right class Cl. This information will be then part of the overall summary Σ.

Each Feature Extractor works with its proper list of features:

- *MOBILITY*: number of times the user left home, total time performing outdoor activities, total time performing activities (both indoors and outdoors), total time of inactivity, covered distance, number of performed steps, number of visited places, number of burned calories.
- *SLEEPING*: total sleeping time, hour the user went to sleep, hour the user woke up, number of times the user went to the toilet during the night, time spent at the toilet during the night, number of time the user went to the bedroom during the night, time spent at the bedroom during the night, number of sleeping hours the day before, number of sleeping hours in the five days before.
- *MOOD*: number of received visits, total time performing outdoor activities, total time performing activities (both indoors and outdoors), total time of inactivity, covered distance, number of performed steps, number of burned calories, hour the user went to sleep, hour the user woke up, number of times the user went to the toilet during the night, time spent at the toilet during the night, number of time the user went to the bedroom during the night, time spent at the bedroom during the night, number of sleeping hours the day before, number of sleeping hours in the five days before. The Classifier is a supervised multi-class classifier built by using data previously labeled by the user and works on five classes, Very Bad, Bad, Normal, Good, and Very Good.

Under the umbrella of BackHome, we tested our approach with 3 users with severe disabilities (both cognitive and motor) living at their own real homes [30]. Although the system was evaluated by using as ground truth answers given to QoL questionnaires that is an approach completely subjective that depends on the particularity of each monitored user, after only 3 weeks of testing, the approach seemed convincing. Results presented in this paper show that *MOBILITY*, *SLEEPING*, and *MOOD* can be inferred with a high accuracy (0.76, 0.72, and 0.81, respectively) by relying on an automatic QoL assessment system. Let us note that *SLEEPING* was the method with the lowest performance. This is due to the fact that, currently, the system uses only motion sensors. Higher performances could be expected when combining motion sensors with other ones, such as mat-pressure or light sensors. *MOBILITY* achieved higher performance results than *SLEEPING* especially when outdoor and indoor features are merged together. In fact, using only outdoor features was not as reliable as combining with indoor. This can be due to the reliability of the GPS system embedded in the smartphone that made some errors in identifying when the user was really away. Let us also note that this is an important result because disable people in general spend a lot of time at their home. Finally, *MOOD* reported the highest performances. Although at a first instance this could be surprising, this fact might be explained considering the intrinsic correlation between *SLEEPING* and *MOBILITY*, as highlighted by the questionnaire compiled daily by the users. It is worth noting that higher performances could be expected considering also social networking activities performed by the user.

4 Users' Experience

The proposed solution has been developed according to a user-centered design approach in order to collect requirements and feedback from all the actors (i.e., end-users and their relatives, professionals, caregivers, and social workers). For evaluation purposes, the system has been installed in two healthy-user homes in Barcelona (control users).

The system has been used in the EU project BackHome to monitor disabled people. BackHome was an European R&D project that focuses on restoring independence to people that are affected by motor impairment due to acquired brain injury or disease, with the overall aim of preventing exclusion [21] [22]. In BackHome, information gathered by the sensor-based system is used to provide context-awareness by relying on ambient intelligence [10]. Intelligent monitoring was used in BackHome to study habits and to automatically assess QoL of people. The BackHome system ran in 3 end-user's home in Belfast.

[6] http://www.cvi-bcn.org/en/

In collaboration with Centre de Vida Independent[7], from May 2015 to January 2016, eKauri was installed in Barcelona in 13 elderly people' homes (12 women) over 65 years old [28]. To test eKauri, monitored users were asked to daily answer to a questionnaire composed of 20 questions (12 optional). Moreover, they daily received a phone-call by a caregiver who manually verifies the data. All detected events were shown in the Web applications and revised by therapists and caregivers. Feedback from them has been used to improve the interface and add functionality.

Although, at least at the beginning, users were a little bit reticent, during the monitored period they felt comfortable with the services provided by eKauri. In particular, they really appreciated the fact that it is not-intrusive and that it allows them to follow their normal lives. In the case of CVI, people also be grateful for being called by phone. In other words, it is important to provide a system that may become part of the home without losing social interactions. Thus, a teleassistance system does not substitute the role of caregivers. On the other side, carers recognized eKauri as a support to detect users' habits helping in diagnosing user's conditions and her/his decline, if any.

Currently, eKauri is installed in 40 elderly people's homes in the Basque Country in collaboration with Fundación Salud y Comunidad[8].

5 Conclusions

Considering the dependency care sector as a case study, in this paper we highlighted how intelligent monitoring techniques, integrated in eKauri, an IoT-based teleassistance system, allow to better provide assistance and support to people that need assistance. In particular, we focused on the power of intelligent monitoring in improving sensor reliability, activity recognition, feedback provided to carers, as well as quality of life of final users. As a matter of fact, results about independent home evaluation of eKauri show a good acceptance of the system by both home users and caregivers. Being promising, the potential socio-economic impact of the exploitation of the system, as well as barriers and facilitators for future deployment, have to be analyzed before going to the market.

Summarizing, our main conclusion is that time is ripe to adopt IoT in the real world and that intelligent monitoring makes the difference in providing feedback to the users. However, to become pervasive, in particular in the dependency care sector, solutions must be taken into account the role of the final users in each phase of the development. Moreover, even if users at home and caregivers give a positive feedback, one step ahead might be performed to allow that stakeholders will take value from third generation teleassistance systems. It means that, as technological providers, we must put into effect concrete solutions that give a twist in adapting innovative strategies.

Acknowledgments

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[7] http://www.cvi-bcn.org/en/
[8] https://www.fsyc.org/

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